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A systematic study on effective demand prediction using machine learning

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ABSTRACT

Effective demand prediction is a crucial aspect of business planning, enabling organizations to optimize their operations and make informed decisions. The advent of big data and machine learning offers new avenues for making precise demand forecasts. This analysis delves into how machine learning algorithms, including regression models, Long Short-Term Memory (LSTM), neural networks, and other advanced techniques, can be employed for this purpose. The discussion will also touch upon the advantages, limitations, and potential future developments in applying machine learning for demand prediction in a business context. Utilizing these methodologies can lead to enhanced decision-making, operational efficiency, and ultimately, a stronger financial performance.

Keywords: Demand Prediction, Business Intelligence, Machine Learning, Data Analysis, Operational Optimization

INTRODUCTION

Understanding customer needs and preferences is increasingly vital due to rapid changes in the marketplace. This insight is crucial for making informed decisions in various areas like marketing, supply chain management, production, and staffing. Key business metrics such as revenue, capital investments, risk assessment, profit margins, and cash flow all hinge on accurate predictions of customer demand. Being able to forecast demand accurately is crucial for calculating expected sales and revenue for a set time frame in the future.[1] In the retail sector, demand forecasting is especially critical. Lack of proper forecasting can lead to inventory imbalances, such as overstocking or understocking products. An excess inventory often forces businesses to offer discounts to move products, affecting profitability.[2,3] On the other hand, stockouts result in missed revenue opportunities. Essentially, demand forecasting involves leveraging historical data through predictive analytics to make educated estimates about future customer needs for a product or service.[4]

Forecasting customer demand is crucial for businesses of all sizes for several key reasons.[5] It offers valuable insights that guide pricing strategies, production schedules, and inventory management. More importantly, it allows companies to identify upcoming trends that could affect their operations. Effective demand forecasting is a cornerstone for enhanced business planning, which can result in higher profits and reduced expenses.

Figure 1 shows some of the significant reasons why demand forecasting is indispensable for businesses of all sizes. Proper demand forecasting ensures that businesses maintain optimal inventory levels, reducing the risk of overstocking or understocking. Such accurate predictions mitigate the need for assumptions that can lead to planning and production mistakes. Avoiding these errors can have an immediate positive impact on a company's financial health.

Moreover, demand forecasting is not just about short-term decision-making; it plays a significant role in long-term strategic planning as well. By providing a clearer understanding of customer behavior and preferences, it allows businesses to be proactive rather than reactive to market changes. Companies equipped with reliable forecasting can fine-tune their strategies to meet both current and future customer needs more effectively.

Businesses in various sectors, including manufacturing and e-commerce, face unique hurdles when it comes to accurate

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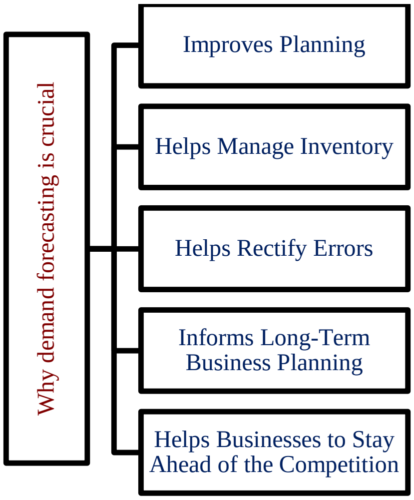

Figure 1. Demand Forecasting Need for Business

forecasting. Online shopping behavior varies considerably from that observed in traditional brick-and-mortar retail settings.[6] The digital landscape is more dynamic and intricate, adding layers of complexity to sales forecasting in e-commerce. In the online setting, consumers often can't physically interact with products before purchase, and their decisions can be heavily influenced by the platform's marketing strategies. These factors contribute to the challenges of predicting sales in the online world.[7,8] Nevertheless, e-commerce platforms have an advantage in that they can easily gather vast amounts of data, which can be leveraged to enhance the accuracy of sales forecasts. Effective demand forecasting can help mitigate these challenges by optimizing inventory turnover rates and providing insights into future consumer buying intentions at specific price points. Over time, researchers have developed various analytical models designed to improve the efficacy of demand and sales forecasting in such complex environments.

The adoption of Artificial Intelligence and Machine Learning (AI-ML) is expanding across a broad range of fields, including Advanced Driver Assistance Systems (ADAS), computer vision, speech recognition, robotics, fintech, healthcare, and more. Increasingly, industries are keen to integrate AI-ML into at least one aspect of their operations to automate processes and gain efficiencies.[9,10] In the realm of supply chain management, the transformation is particularly noteworthy. AI-ML technologies are being employed across multiple facets of the supply chain, enhancing everything from demand forecasting and logistics to inventory management, production planning, and procurement. The digitalization of these areas through AI-ML not only streamlines operations but also introduces new levels of accuracy and predictive power, ultimately contributing to more effective and efficient supply chain practices.

Machine learning (ML) is revolutionizing the field of demand forecasting by addressing many of its traditional challenges, such as extended delivery lead times, elevated transportation costs, excessive inventory, and decision-making errors stemming from inaccurate projections.[11] One of the key benefits of implementing ML in demand forecasting is the enhancement of accuracy. By drawing from large sets of historical data related to past sales, products, and forecasts, ML models can make remarkably accurate predictions.[12] Moreover, the use of ML in forecasting frees up valuable time for demand planners. Rather than getting bogged down with manual calculations and estimates, planners can allocate their time more effectively, focusing on high-priority products or gathering last-minute data to refine forecasts further.[13] ML technology is both pervasive and iterative. The sooner it's implemented, the faster its algorithms can be fine-tuned to generate business benefits. Beyond cost savings and process optimization, ML's impact extends to improving customer satisfaction, particularly when applied thoughtfully to solve the right problems.[14] This shows that the technology is not just about enhancing operational efficiency but also about enriching the overall customer experience.

The objective of a review paper on machine learning-based demand forecasting in different business applications

1. Provide an in-depth analysis of current research and practice in machine learning-based demand forecasting.
2. Reviewed different types of machine learning models used for demand forecasting.
3. Discuss the advantages and challenges associated with implementing machine learning models for demand forecasting.
4. Identify challenges in research and suggest future directions for research and practice.
5. Provide a comprehensive and informative overview of the current state of the field.

ML-Based Demand Forecasting

Demand forecasting through machine learning (ML) employs computational algorithms and statistical methodologies to examine past data for predicting future demand. Businesses utilize historical data to train ML models, which then discern patterns and trends. These models subsequently provide insights for projecting upcoming demand. Below are the steps (as shown in Figure 2) we adhere to for forecasting demand using machine learning:

Step 1. Brief data review

The initial phase of a demand forecasting project involves offering valuable insights to the client. To begin, it's essential to scrutinize various data sources related to demand, such as historical sales figures, customer behavior metrics, and other pertinent data sets.[15,16] This examination aids in pinpointing patterns and trends that can shape the predictive model. The procedure encompasses the following steps:

1. Gather available data
2. Briefly review the data structure, accuracy, and consistency
3. Run a few data tests and pilots
4. Look through a statistical summary
5. In our experience, a few days is enough to understand the current situation and outline possible solutions.

Step 2. Setting business goals and success metrics

The subsequent step entails outlining the business objectives for the demand forecasting model and setting up metrics to evaluate its efficacy. For instance, the objective might be to precisely forecast demand for a particular product or service, with success indicators like forecast accuracy, precision, recall, or other pertinent metrics.

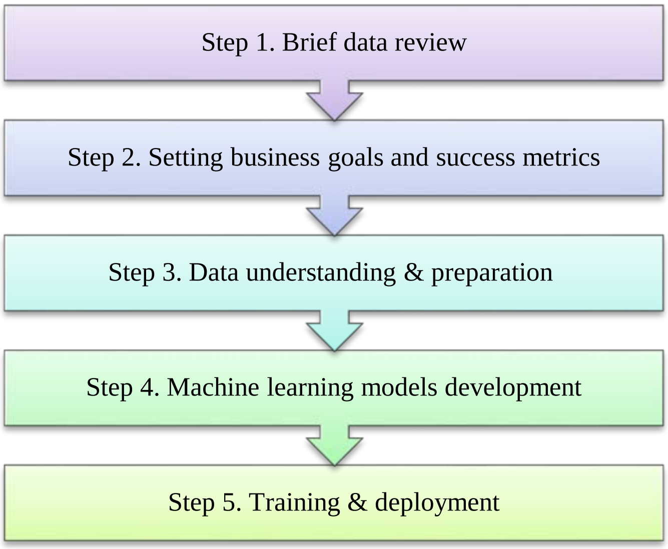

Figure 2. Steps for Demand Prediction

Each project is distinct and comes with its own set of business objectives.[17] This phase is crucial for devising a successful forecasting solution, as it sets the stage for the development process and guides subsequent phases. Before embarking on the development of a demand forecasting solution, the software development team must reach a consensus with the client or business owner on the metrics that will be used to assess the model's performance. These metrics serve as a definitive guide for what is considered "valuable" in the realm of demand forecasting.

Step 3. Data understanding & preparation

At this stage, the data undergoes preparation and analysis for its incorporation into the machine learning model. This involves data cleansing, outlier removal, reformatting the data into a utilizable structure, and feature engineering to enhance the model's accuracy.[18] Regardless of the specific outcomes we aim to forecast, the quality of the data is a pivotal factor in generating accurate demand predictions. The types of data that can be utilized for constructing forecasting models are as follows:

Step 4. Machine learning models development

The subsequent phase focuses on constructing machine learning models tailored for demand forecasting. This includes choosing a suitable algorithm—ranging from linear regression and time series analysis to neural networks—and training it on the processed data. The step may also require fine-tuning hyperparameters like learning rate or regularization strength to optimize the model's effectiveness.[19,20] There's no universal algorithm that serves all forecasting needs; typically, demand forecasting employs a mix of various machine learning techniques. The selection of the appropriate machine learning models hinges on multiple factors such as business objectives, types of data, data volume and quality, and the time horizon for forecasting.

Following are the different machine learning approaches that can be used for most demand forecasting cases:

1. Regression models
2. XGBoost
3. K-Nearest Neighbors Regression
4. Random Forest
5. Long Short-Term Memory (LSTM).

Step 5. Training & Deployment

In the final stage, the machine learning model undergoes training using the refined data and is subsequently assessed based on the predetermined success criteria. Once the model has proven to be both accurate and reliable, it is ready for deployment to execute demand forecasting for the business. Continuous monitoring and periodic updates are essential to maintain the model's accuracy and adapt it to changing conditions over time.

1. Training: In this phase, data scientists typically utilize historical data to train forecasting models. The algorithms process this data to yield one or more trained models ready for application.
2. Validation: The objective here is to fine-tune the model parameters for optimal performance. Data scientists employ cross-validation techniques, dividing the training dataset into several equal segments, to train various models using different hyperparameters. The aim is to determine which set of model parameters delivers the most accurate forecasts.
3. Improvement: During the search for optimal business solutions, data scientists often construct multiple machine learning models, selecting those that best meet the project's criteria. This enhancement stage focuses on refining the analytical outcomes. For instance, ensemble methods can be used to amalgamate the results of several models, thereby improving forecast accuracy.
4. Deployment: At this point, the vetted forecasting model(s) are integrated into a production environment. It's advisable to establish a data pipeline to collect new information for future AI-driven features. This not only streamlines data preparation for upcoming projects but also augments the range and precision of potential forecasts.

LITERATURE REVIEW

The application of machine learning and deep learning in the domain of sales forecasting has garnered significant attention in recent years. A plethora of research has been conducted to tackle various forecasting challenges, ranging from stock requirement predictions to customer demand, food demand, and more. This literature review aims to elucidate the different approaches and models that have been proposed and implemented in the field, with a focus on their efficacy and predictive accuracy.

Nithin et al.[18] designed a deep learning-based model to predict stock requirements for retail stores using historical sales data. The study incorporated the Swish Activation Function, surpassing the performance of the commonly used ReLU (Rectified Linear Unit) function. The model outperformed various other architectures like Multilayer Perceptrons (MLP), Long Short-Term Memory (LSTM) cells, and Convolutional Neural Networks (CNNs), with CNN-LSTM model reporting the lowest RMSE.

Lutoslawski et al.[19] developed models for predicting food demand, focusing on processed food items. Their nonlinear autoregressive exogenous neural network (NARXNN) models displayed variations in predictive performance based on product types, achieving high R2 measures ranging from 96.2399 to 99.6477.

Chen et al.[20] evaluated a Neural Network model for Walmart's sales prediction, achieving a lower RMSE compared to traditional machine learning algorithms like Linear Regression and Support Vector Machines (SVM). They also employed SHAP (SHapley Additive exPlanations) for model interpretation.

Pérez et al.[21] tackled customer sales forecasting at day/store/item level with machine learning and deep learning techniques. Their sequence-to-sequence architecture with minimal data preprocessing efforts achieved competitive RMSLE scores around 0.54.

Ensafi et al.[22] explored various forecasting models, including Prophet and CNN, for predicting retail furniture sales. The Stacked LSTM approach outperformed other methods based on RMSE and MAPE metrics. Similarly, Saha et al.[26] compared LSTM and LGBM models in sales forecasting, with LGBM showing better performance on multiple accuracy metrics.

Rohaan et al.[23] leveraged advanced demand information in B2B sales forecasting using supervised machine learning and Natural Language Processing (NLP). The model outperformed manual methods by over 2.5 times in terms of precision and recall.

Qiao et al.[27] introduced a Particle Swam Optimization (PSO) metaheuristic to optimize LSTM layers for sales forecasting in E-commerce. The novel approach outperformed nine competing approaches in terms of forecasting accuracy.

Schmidt et al.[24] employed machine learning models in restaurant sales forecasting. Linear models excelled in one-day forecasting with low sMAPE, whereas RNN models performed better for extended forecasts. Hamzehi et al.[29] employed machine learning to optimize pharmaceutical sales using clustering methods. The K-means algorithm provided optimal results in this context.

Zhao et al.[25] applied XGBoost and Random Forest algorithms for purchase prediction, achieving an F1-score of around 0.789. Tsilingeridis et al.[28] introduced the MULTIFOR framework for macroeconomic forecasting, reducing errors by approximately 70% in time-series data.

Punia et al.[31] proposed a model for demand forecasting based on big data, outperforming benchmarking methods across multiple error metrics. Khan et al.[32] demonstrated the effectiveness of machine learning for enterprise demand forecasting, achieving up to 92.38% accuracy.

RESEARCH GAPS

The provided literature offers a comprehensive look at various approaches to sales forecasting and demand prediction, leveraging machine learning and deep learning algorithms. Despite the extensive research, several research gaps can be identified:

Temporal Coverage

Time Sensitivity: While some papers consider temporal effects, there is limited discussion on how models adapt to rapidly changing market conditions or trends, especially in real-time scenarios.

Methodological Aspects

Model Interpretability: While papers like that of Chen et al.[20] mention the use of SHAP for model interpretation, there's a lack of comprehensive study on the interpretability of these complex models, which is crucial for business decision-making.

Comparative Analyses: While individual papers present the efficacy of their chosen methods, there is less emphasis on comparative studies that juxtapose various machine learning algorithms for the same dataset, considering multiple performance metrics.

Data Quality: None of the papers appear to delve into the impact of the quality of historical sales data, such as missing values or outliers, on forecast accuracy.

Application Domains

Industry-Specific Models: Although some studies focus on specific sectors like food or pharmaceuticals, there is a gap in research addressing the generalizability or adaptability of these models across different industries.

Small and Medium Enterprises (SMEs): Most studies focus on large corporations or publicly available datasets. There is a gap in research tailored to the unique challenges and limited data availability in SMEs.

Performance Metrics

Real-world Validation: While metrics like RMSE, MAE, etc., are extensively used, there is less focus on the real-world applicability and the financial impact of the prediction errors.

Technological Aspects

Scalability and Efficiency: Few papers, if any, discuss the computational cost and scalability of their proposed models, which is a critical aspect of real-world applications.

Integration with Existing Systems: The literature doesn't discuss how these machine learning models integrate with existing inventory management or enterprise resource planning systems.

Societal and Ethical Concerns

Sustainability and Waste Reduction: While Lutoslawski et al.[19] mention the reduction of food waste, there's a general absence of discussion on how predictive analytics could contribute to sustainability goals.

Emerging Technologies

Inclusion of Emerging Technologies: There is no mention of leveraging newer technologies like edge computing or IoT sensors for real-time data collection and analytics.

User Experience

User-Centric Models: Customer behavior and preferences could offer valuable context, but the existing literature seems more product-centric than user-centric.

Interdisciplinary Studies

Macroeconomic Factors: Papers like that of Tsilingeridis et al.[28] touch upon macroeconomic variables, but there's a gap in comprehensive studies that consider external macroeconomic factors affecting sales.

Addressing these research gaps could provide more insightful, adaptable, and actionable solutions for sales forecasting and demand prediction.

DISCUSSION

A variety of machine learning models have been employed in demand forecasting, as summarized in Table 1.

Each has its strengths and weaknesses, often manifested in performance metrics like RMSLE, sMAPE, F1-score, and RMSE among others. ANNs, as mentioned by Shatashawa et.al.[30], can be considered a more "general-purpose" approach. They're effective but may not be the best for capturing temporal or sequential patterns without being specifically designed to do so.

Table 1. Recent Research Contributions

Ref	Method	Result
[21]	Recurrent Neural Networks	RMSLE of around 0.54
[22]	LSTM AND CNN	results indicate the good performances
[23]	supervised machine learning	identifies ~ 70% of actual sales (recall) with a precision rate of ~ 50%
[24]	RNN models, LSTM and TFT	sMAPE scores giving 19.5% in the best result
[25]	XGBoost and Random Forest machine learning	F1-score around 0.789
[26]	LSTM and Light GBM	LGBM and LSTM has RMSE 4436 and 2125.28, MAE around 5024 and 2379.06
[30]	Artificial Neural Network (ANN)	MAD is 22.22, MAPE is 15.4010, MSE is 993.726
[31]	Deep learning based system	(ME= 0.11248), accuracy (MAE= 1.74), and variance(RMSE=2.27)
[32]	Different ML algorithm	achieved good results in demand forecasting, 92.38 % accuracies

Deep learning models[31] are pushing the envelope further in terms of accuracy. However, they often require even larger datasets and more computational power, not to mention the challenges tied to interpretability. The earlier studies[21,24] have delved into the power of Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) models. These neural architectures excel at capturing temporal dependencies, making them ideal for time-series data often found in demand forecasting. While their performance is generally promising, as demonstrated by an RMSLE of 0.54,[21] they can computationally be intensive. Their "black-box" nature can also make it difficult to interpret how the model arrived at a specific forecast, which could be a crucial limitation for stakeholders. The success of XGBoost and Random Forest in achieving an F1-score of around 0.789,[25] reveals the robustness of tree-based algorithms.

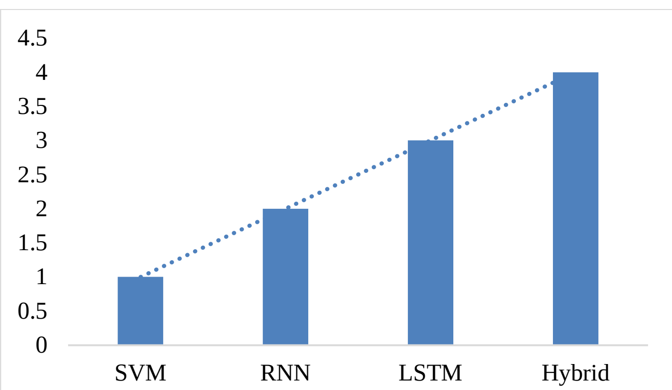

Figure 3. Trendline of Machine Learning Approaches for Demand Prediction

These models offer a good trade-off between interpretability and performance. However, they might not capture temporal dependencies as effectively as RNNs or LSTMs. Therefore, they might be more suited for situations where the temporal sequence is less critical. The use of LSTM combined with other methods like Light GBM and CNN[22,26] has shown that hybrid models can potentially offer the best of both worlds - high performance and feature interpretability. This is particularly appealing when dealing with complex, multi-dimensional data. Nevertheless, these models can be complex to tune and require considerable expertise. According to this discussion, a trendline of model is presented in figure 3.

Advantages and Challenges Of Demand Forecasting Using Machine Learning For Different Business Applications

Machine learning models have great advantages over traditional techniques of demand forecasting as shown in Fig 4, they can analyze large amounts of historical data and identify patterns that humans may not be able to detect. This can lead to more accurate demand and sales forecasts. Machine learning models can be easily scaled to handle large amounts of data and can be adapted to different business applications. This can quickly generate insights and predictions, allowing businesses to make decisions faster and more confidently. Automated forecasting using machine learning models can save time and reduce errors compared to manual forecasting methods.

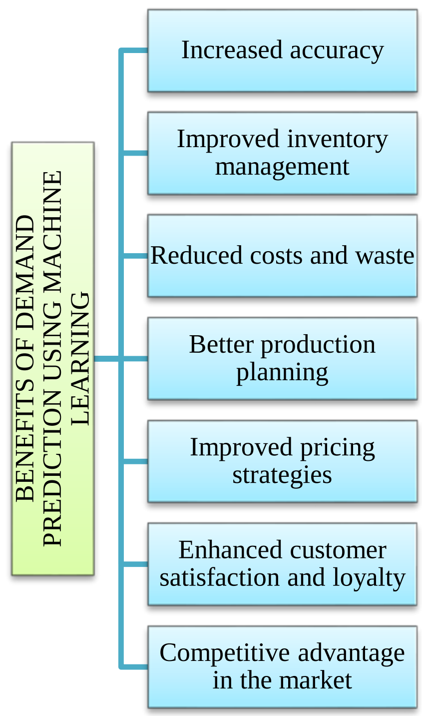

Figure 4. Benefits of Demand Prediction Using Machine Learning

Machine learning-based demand forecasting has become an essential tool for businesses of all sizes to predict future customer demand and sales trends. However, there are several challenges that businesses need to consider when implementing these models. One of the biggest challenges is data quality. Machine learning models require large amounts of historical data to generate accurate predictions, but if the data is incomplete, inaccurate, or biased, the forecasts may be unreliable. Another challenge is the complexity of the models themselves. Machine learning models can be difficult to understand, making it challenging for businesses to interpret the results and make decisions based on them. Additionally, implementing machine learning models requires technical expertise in data science and programming, which can be a challenge for businesses that lack these skills. Privacy and ethical concerns can also be a challenge, particularly if the data being used includes personal or sensitive information. Finally, businesses need to ensure that their machine-learning models are regularly updated and refined to keep up with changes in customer behavior and market trends. Despite these challenges, machine learning-based demand forecasting offers businesses the opportunity to improve accuracy, scalability, and efficiency, and it is likely to continue to play a crucial role in future business applications.

Future Scope

Machine learning-based demand forecasting has rapidly become a critical tool for businesses in various industries to predict future customer demand and sales trends. The future scope of machine learning-based demand forecasting is vast and promising. One of the most exciting applications is enhanced personalization.[33] Machine learning models can be used to personalize recommendations and promotions based on individual customer behavior, leading to more effective marketing and higher sales[34]. Following are the future scopes of demand forecasting using machine learning:

1. Enhanced personalization: Machine learning models can be used to personalize recommendations and promotions based on individual customer behavior, leading to more effective marketing and higher sales.
2. Improved supply chain management: Machine learning models can be used to optimize inventory management, reduce waste, and minimize stockouts, leading to more efficient supply chain management.
3. Increased automation: Machine learning models can be used to automate many aspects of demand and sales forecasting, reducing the need for manual intervention and saving time and resources.
4. Integration with other technologies: Machine learning can be integrated with other technologies such as IoT devices and blockchain to improve data quality and accuracy, leading to more reliable forecasts.

Conclusion

Accurately predicting demand is critical for businesses to remain competitive and optimize their operations. By utilizing machine learning-based business intelligence data analysis, historical data can be analyzed, and patterns and trends can be identified to forecast future demand with precision. This research paper explores the use of machine learning-based business intelligence data analysis for effective demand prediction. The results show that the use of machine learning-based business intelligence data analysis can provide businesses with a range of benefits, including improved inventory management, better production planning, enhanced customer satisfaction and loyalty, and a competitive advantage in the market. However, there are also some challenges associated with the use of these techniques, such as data quality, data privacy, and model interpretability. Future research can explore ways to address these challenges and further improve the effectiveness of machine learning-based demand prediction techniques in businesses.

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